

## Chapter IV

# Revealing Social Structure from Texts: Meta-Matrix Text Analysis as a Novel Method for Network Text Analysis<sup>i</sup>

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### Abstract

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*Texts can be coded and analyzed as networks of concepts often referred to as maps or semantic networks. In such networks, for many texts there are elements of social structure — the connections among people, organizations, and events. Within organizational and social network theory an approach called the meta-matrix is used to describe social structure in terms of the network of connections among people, organizations, knowledge, resources, and tasks. We propose a combined approach using the meta-matrix model, as an ontology, to lend a second level of organization to the networks of concepts recovered from texts. We have formalized and operationalized this approach in an automated tool for text analysis. We demonstrate how this approach enables not only meaning but also social structure to be revealed through text analysis. We illustrate this approach by showing how it can be used to discover the social structure of covert networks — the terrorist groups operating in the West Bank.*

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## **Introduction**

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Texts are a typical source of information about meaning, organizations, and society. Today, a large and growing number of texts are available in an electronic form that describes, discusses, or displays information about people, the groups to which they belong, the activities in which they engage, and the resources at their disposal. This data and its accessibility motivate the development and investigation of automated techniques for extracting the underlying social and organizational structure from such texts in an effective and efficient way.

In this chapter, we present an automated approach to text analysis that can be used to extract the underlying social and organizational structure contained in texts. This approach is based on the following insights. First, texts can be represented as networks of concepts and the connections between them. These concepts refer to ideas, people, resources, organizations, events, etc. Second, many of the items referred to, such as people, are core entities in the structure of groups and organizations. Hence, the extracted networks contain representations of the social structure — the entities and relations among them that comprise a group, organization, or society. By classifying the concepts into entity classes used in defining social structures and partitioning the extracted network into sub-networks, we have effectively used network analysis of texts to reveal the social structure represented in texts.

Herein, we describe this approach in detail and explain how we operationalized, formalized, and implemented it into a software called AutoMap that enables analysts to extract social structure from texts. As part of this work, we have operationalized an ontological scheme based on the meta-matrix proposed by Carley (2002) for describing social and organizational structure. This ontology is utilized as part of a hierarchical scheme for cross categorizing concepts. In this chapter we furthermore demonstrate how analysts can use AutoMap to automatically extract not just networks of concepts and the relations among them, but also classify the concepts and relations between them according to this ontology. This enables the automatic extraction of views of the social structure.

The chapter begins with a brief overview on the model and methods involved. We then describe how we formalized and implemented the combination of the meta-matrix model and the network text analysis technique. This is followed by a substantive example that we provide in order to illustrate this approach for revealing social structure through the analysis of texts by extracting an image of the social structure of the terrorists groups in the West Bank. We conclude with a discussion of the potentials and limitations of our approach.

Note, this chapter should not be viewed as a description of the West Bank terrorist groups. We have coded for this chapter only a small sample of texts to illustrate the technique. No conclusions for this group should be drawn from the results reported herein.

## Using Network Text Analysis to Code Texts

In the area of network text analysis, previous research and development have provided computer-supported solutions that enable analysts to gain a window into social structure and meaning as represented in texts. Collectively these approaches enable the analyst to extract networks of concepts and the connections between them from the texts. These networks are sometimes referred to as maps (Carley, 1997b), networks of centering words (Corman, Kuhn, McPhee & Dooley, 2002), semantic nets (Reimer, 1997), semantic networks (Monge & Contractor, 2001, 2003; Popping, 2003; Ryan & Bernard, 2000), networks of concepts (Popping, 2000), or networks of words (Danowski, 1993). Herein, we refer to such techniques using the general term — network text analysis (NTA) (Carley, 1997b; Popping, 2000). NTA approaches vary on a number of dimensions such as the level of automation, a focus on verbs or nouns, the level of concept generalization, and so on. Nevertheless, in all cases, networks of relations among concepts are used to reveal the structure of the text, meaning, and the views of the authors. Further, these networks are windows into the structure of the groups, organizations and societies discussed in these texts. This structure is implicit in the connections among people, groups, organizations, resources, knowledge tasks, events, and places.

NTA is a specific text analysis method that encodes the links between words in a text and constructs a network of the linked words (Popping, 2000). The method is based on the assumption that language and knowledge can be modeled as networks of words and the relations between them (Sowa, 1984). NTA methodologically originates from traditional techniques for indexing the relations between words, syntactic grouping of words, and the hierarchical and non-hierarchical linking of words (Kelle, 1997). The method of NTA enables the extraction, analysis, and concise representation of the complex network structure that can be represented in texts. Furthermore, NTA covers the analytic spectrum of classical content analysis by supporting the analysis of the existence, frequencies, and covariance of words and themes (Alexa, 1997; Popping, 2000). Given these functionalities, computer-supported NTA is a suitable method for analyzing large collections of texts effectively and efficiently. Several NTA methods exist (see bullet items listed below; for more details on methods, see Popping, 2000; Popping & Roberts, 1997). Many have been applied in empirical settings (see discussion by Monge & Contractor, 2003) such as:

- Centering Resonance Analysis (Corman et al., 2002)
- Functional Depiction (Popping & Roberts, 1997)
- Knowledge Graphing (Bakker, 1987; James, 1992; Popping, 2003)
- Map Analysis (Carley, 1988, 1997b; Carley & Palmquist, 1992)
- Network Evaluation (Kleinnijenhuis, Ridder & Rietberg, 1996)
- Word Network Analysis (Danowski, 1982).

Besides the analysis of textual data, current work also focuses on the visualization of networks extracted from texts (Batagelj, Mrvar & Zaveršnik, 2002).

In this research we concentrate on map analysis. Map analysis systematically extracts and analyzes the links between words in texts in order to model the authors "mental maps" as networks of linked words. Coding texts as maps focuses analysts on investigating the meaning of texts by detecting the relationships between and among words and themes (Alexa, 1997; Carley, 1997a). Maps are a cognitively motivated representation of knowledge (Carley, 1988). In map analysis, a concept is a single idea represented by a single word or a phrase. A statement is two concepts and the relation between them. A map is the network of the statements (Carley, 1997b).

Before continuing, it is worth noting that the terminology in this area is very diverse, having come from a variety of disciplines. Thus to orient the reader and help avoid confusion, we provide some basic terminology as we will use it herein in Table 1. This will foreshadow the discussion of the procedure we are proposing in this chapter.

Table 1. Terminology and associated symbols

Term	Definition	Alternative Terms	Examples
Text	A written work.	Sample	Newspaper article, abstract, Web site, interview
Text-level concept	Words that appear in text	Word, concept, phrase, named-entity	Rantissi, Palestine, Hamas, terrorism, captured
Higher-level concept	A word or phrase chosen by the analyst into which other words or phrases are generalized	Concept, node	Terrorist, Osama bin Laden
Concept	Single ideational kernel	Node	Terrorism, terrorist, Friday, 9-11
Entity class	Objective category that can be used for classifying concepts; Top level in the ontology	Meta-node, entity, category, concept type, node type	People, Organizations
Relation	Connection between concepts	Link, tie, edge, connection	Rantissi is in the Hamas
Relation class	Objective category that can be used for classifying relations connecting concepts in entity class "a" to concepts in entity class "b," such that "a" and "b" may or may not be distinct.	Relation type, Edge type, Tie type, sub-network	Social network, is a member of
Map	The network formed by the set of statements (two concepts and the relation between them) in a text.	Network, concept network, semantic network, network of concepts	See Figures 3 and 4
Meta-matrix	Conceptual organization of concept networks into a set of networks defined by entity classes and relation classes	Ontology, classification scheme, meta-network	See Tables 2 and 3

## Using the Meta-Matrix as an Ontology

Since NTA can be used to extract networks of concepts, we can leverage the methods of social network analysis (SNA) to analyze, compare and combine the network of concepts extracted from the texts (see e.g., Scott, 2000; Wasserman & Faust, 1994 for SNA techniques). This provides the analyst with tremendous analytical power (see Hill & Carley, 1999 for illustrative study). If in addition, we cross classify the extracted concepts into an ontology, particularly one designed to capture the core elements of social and organizational structure, we gain the added theoretical power of extracting in a systematic fashion an empirical description of the social and organizational structure. The key would be to design a useful ontology.

Such an ontology is implicit in the meta-matrix approach (Carley 2003, 2002; Krackhardt & Carley 1998) to organizational design. Krackhardt and Carley defined an approach to represent the state of an organizational structure at a particular point in time as the set of entities (people, resources, and tasks) and the relations among them. The meta-matrix approach is a representational framework and a set of derived methods for the computational analysis of multi-dimensional data that represents social and organizational systems. The concept of the meta-matrix originates from the combination of:

1. Information processing and knowledge management (Carley & Hill, 2001; Galbraight, 1977; March & Simon, 1973).
2. The PCANS approach (Krackhardt & Carley, 1998), which was later generalized by Carley and Hill to include knowledge, events, and organizations (Carley, 2002; Carley & Hill, 2001).
3. Operations research (Carley & Krackhardt, 1999; Carley, Ren & Krackhardt, 2000).
4. Social network analytic techniques and measures (see e.g., Scott, 2000; Wasserman & Faust, 1994).

The meta-matrix enables the representation of team or organizational structure in terms of entity classes and relations. In principle, this is an extensible ontology such that new entity classes and new classes of relations can be added as needed. Each entity class represents an ontologically distinct category of concepts (or in the social network language, nodes). Each relation class is a type of link between concepts within entity class 1 and 2. For the sake of illustration, we use a simple form of the ontology in which we identify four entity classes — People, Resources (or Knowledge/Skills), Tasks or Events, and Groups or Organizations (see Table 2 headers). We choose these entity classes as they are sufficient for illustration and they are critical for understanding the structure of teams, groups and organizations. The reader should keep in mind that it is possible to use different entity classes and still think in terms of the meta-matrix conceptualization (as we do in this chapter). The key aspect for our purposes is that the meta-matrix defines a set of entity classes and a set of relation classes. This facilitates thinking systematically about organizational structure and provides a limited hierarchy for structuring the network of concepts.

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focuses on the visualization of (Šnik, 2002).

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logy in this area is very diverse, orient the reader and help avoid will use it herein in Table 1. This re proposing in this chapter.

Terms	Examples
Concept, phrase, entity	Newspaper article, abstract, Web site, interview Rantissi, Palestine, Hamas, terrorism, captured
Node	Terrorist, Osama bin Laden
Edge, relationship, entity, concept type	Terrorism, terrorist, Friday, 9-11 People, Organizations
Edge, relationship, entity, concept type	Rantissi is in the Hamas
Edge, relationship, entity, concept type	Social network, is a member of
Concept semantic network of	See Figures 3 and 4
Classification meta-network	See Tables 2 and 3

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Table 2: Original meta-matrix conceptualization

Meta-Matrix entities	People	Knowledge/ Resources	Events/ Tasks	Groups/ Organizations
People	Social network	Knowledge Network/ Resource Network	Attendance Network/ Assignment Network	Membership network
Knowledge/Resources		Information Network/ Substitution Network	Needs network	Organizational capability
Events/Tasks			Temporal Ordering/ Task Flow/ Precedence	Institutional support or attack
Organizations				Interorganizational network

Based on Carley (2002, 2003)

Between any two entity classes there can be one or more classes of relations. For example, between people and people we can think of a number of relations including, but not limited to, communication relations, friendship relations, or money/exchange relations. To orient the reader, in Table 2, common labels for the network formed by linking the row and column entity classes are identified. The data in a meta-matrix represents the structure of the group or organization at a particular time. It can be analyzed to locate vulnerabilities, strengths, features of the group, to identify key actors, and to assess potential performance. In summary, the meta-matrix approach allows analysts to model and analyze social systems according to a theoretically and empirically founded schema (Carley, 2003). By employing this approach as an ontology, we enable the analyst to extract and analyze social systems as described in texts.

## Combining NTA and Meta-Matrix Approaches

In texts, the links between words (concepts) are implicit. Hence, extracting a network of concepts from a text, and classifying this network via the meta-matrix ontology, requires an inference process. The links, or relations, between concepts must be extracted based on the semantic, syntactic, and contextual information given in a text (Carley, 1986; Carley, 1988; Popping, 2003). Making the meta-matrix approach available for NTA can provide analysts with a novel technique for extracting textual networks that reveal the relationships within and between the elements that compose a network and that were classified *a priori* according to the meta-matrix model. The features of the textual data that are relevant to the analyst can then be represented as a network structure of the meta-

matrix entity classes and the connections between these classes. Such a network makes the structure of social systems, which is implicitly contained in texts visible and analyzable.

How did we combine and formalize the meta-matrix approach and map analysis technique, which is a specific type of NTA? We utilized the meta-matrix model as an extension of NTA in general and map analysis in specific by instantiating the following five step procedure:

1. **Concept Identification:** identify the concepts in texts that are relevant to the analyst's research question. As part of this process, the analyst may first want to generalize many text-level concepts into higher-level concepts.
2. **Entity Identification:** define an ontology for capturing the overall structure described in the text. We use the basic meta-matrix. Other analysts may wish to adapt this to their research question. Note, step 1 and 2 can also be done in reverse order.
3. **Concept Classification:** classify the identified concepts into the relevant entity classes in the meta-matrix. Given the vagaries of the language it may be that some concepts need to be cross-classified in two or more entity classes.
4. **Perform Map Analysis:** automatically extracting the identified concepts and the relations among them from the specified texts. This results in a map or conceptual network. Since the concepts are classified by entity classes, the resulting concept network is hierarchically embedded in the ontology provided by the meta-matrix. In essence then, there are three networks. First, there is the concept network where the nodes are concepts (many of which are higher-level concepts). Second, there is the entity network where the nodes are the entity classes and the links are the connections among and between the entity classes. Third, there is the network embodied in the meta-matrix thesaurus, connecting concepts in entity classes to concepts in the same or other entity classes.
5. **Graph and Analyze Data:** the final step is to take the extracted data for each text, the network, and graph and analyze it in general and by cells in the meta-matrix. As part of this analysis, the resultant networks from different texts can be combined and compared. Note the analysis can occur at the concept network level (map analysis), the entire meta-matrix level (meta-matrix text analysis), and the sub-cell level (sub-matrix text analysis).

We refer to these five steps as the method of meta-matrix text analysis. With this novel technique we hope to contribute towards the analysis of complex, large-scale data and social systems and providing profound multi-level access to the meaning of textual data. We note that these steps begin to bridge the gap between NTA and a more interpretive analysis of texts. The meaning of concepts is revealed by virtue of other concepts they are connected to. In the meta-matrix approach, the meaning of concepts is revealed both by what other concepts they are connected to and by what type of entity classes into which they fall.

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Groups/ Organizations
Membership network
Organizational capability
Institutional support or attack
Interorganizational network

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## Implementation of Meta-Matrix Text Analysis

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We have implemented our formalization of the technique of meta-matrix text analysis in a network text analysis tool called AutoMap (Diesner & Carley, 2004). AutoMap is a software application that helps analysts to extract, analyze, represent, and compare mental models from texts. The tool performs computer-supported content analysis, map analysis, meta-matrix text analysis, and sub-matrix text analysis. The latter two types of analysis we discuss in this section. The more classic content analysis and map analysis were previously described in Carley and Palmquist (1992) and Carley (1997a).

Steps 1 to 3 in meta-matrix text analysis may involve a thesaurus. A thesaurus in general is a two-columned collection that associates text-level concepts with higher-level concepts (Burkart, 1997; Klein 1997). The text-level concepts represent the content of a data set, and the higher-level concepts represent the text-level concepts in a generalized way. Thesauri are created by reading a set of texts, using pre-defined material, and/or deriving pairs of concepts and higher-level concepts from theory (Burkart 1997; Kelle 1997; Klein, 1997; Zuell & Alexa 2001). The terminology of a thesaurus depends on the content and the subject of the data set.

Thesauri play a key role in any AutoMap coding. AutoMap in performing content analysis or map analysis can utilize a generalization thesaurus. In this thesaurus, the analyst can reclassify words in relation to other words on the basis of shared meaning, spelling errors, aliases, etc. Further, phrases that refer to a single ideational kernel — such as “Weapons of Mass Destruction” — can be reclassified as a single concept — WMD. When texts are pre-processed by AutoMap, using a generalization thesaurus, idiosyncratic differences in writing style, multi-word-concepts and wording errors can be eliminated. This generalization process facilitates identifying true conceptual similarities and differences across texts. The creation of the generalization thesauri is step 1, concept identification, in the coding procedure.

When AutoMap is used to perform a meta-matrix text analysis, a second type of thesaurus can also be employed. This second thesaurus, the meta-matrix thesaurus, contains the translation of concepts into the entity classes in the meta-matrix. When texts are processed with a meta-matrix thesaurus, the organizational structures described in the text can be extracted. Since one concept might be indicative of several meta-matrix entity classes, a meta-matrix thesaurus can consist of more than two columns. For example, the concept military falls into two entity classes — Organization and Resource. The specific entity and relation classes used for the meta-matrix approach in this chapter are presented in Table 3.

Note that in applying the meta-matrix conceptualization to terrorist groups, we have extended the original conceptualization (see Table 2) by treating Knowledge and Resource as separate entities (Carley & Reminga, 2004) and by adding Location as a primary entity. Further, we generalized people into Agent to reflect the fact that often names are not known and people are identified by actions such as “victim killed.” Since this is an extensible ontology, these changes pose no harm to the underlying theory. We did this extension as knowledge, resources, and location are meaningfully unique entities



## Matrix Text

meta-matrix text analysis in Carley, 2004). AutoMap is a technique to analyze, represent, and compare network content analysis, map analysis. The latter two types of network analysis and map analysis are described by Carley (1997a).

AutoMap is a thesaurus in general terms that represents the content of a network of concepts in a generalized network of re-defined material, and/or network theory (Burkart 1997; Kelleher 1997). A thesaurus depends on the

AutoMap in performing content analysis. In this thesaurus, the network is based on shared meaning, a single ideational kernel — such as a single concept — WMD. Generalization thesaurus, idiosyncratic and wording errors can be corrected. True conceptual similarities on thesauri is step 1, concept

AutoMap is a second type of thesaurus, a meta-matrix thesaurus, contains the network meta-matrix. When texts are analyzed, the network structures described in the network of several meta-matrix entity classes are shown in columns. For example, the network Agent and Resource. The specific network in this chapter are presented

AutoMap to terrorist groups, we have analyzed by treating Knowledge and Resource and by adding Location as a network to reflect the fact that often network such as “victim killed.” Since network to the underlying theory. We network meaningfully unique entities

Table 3. Meta-matrix model formalization used in AutoMap — entity classes and relation classes

Meta-Matrix Entities	Agent	Knowledge	Resources	Tasks/Event	Organizations	Location
Agent	Social network	Knowledge network	Capabilities network	Assignment network	Membership network	Agent location network
Knowledge		Information network	Training network	Knowledge requirement network	Organizational knowledge network	Knowledge location network
Resources			Resource network	Resource requirement Network	Organizational Capability network	Resource location network
Tasks/ Events				Precedence network	Organizational assignment network	Task/Event location network
Organizations					Inter-organizational network	Organizational location network
Location						Proximity network

AutoMap for research in the area of covert networks. By extending the meta-matrix as shown in Table 3, we have done step 2, entity identification, of the coding procedure.

The analyst can use none, one or both types of thesauri, generalization and meta-matrix, to analyze texts with AutoMap. In general, the analyst may find it useful to first create a word list, then a generalization thesaurus, then a meta-matrix thesaurus. Building these thesauri can be done iteratively as new texts are added to the available set, as AutoMap minimizes the cost of coding and recoding texts. The larger the corpus of texts being analyzed, the more time is saved.

When using the meta-matrix thesaurus, AutoMap allows the analyst to associate a text-level concepts or higher-order concepts from the generalization thesauri with one, multiple or no entity classes, and to add user-defined entity classes. This process of associating concepts with entity classes is step 3, concept classification, in the coding procedure.

When AutoMap applies the meta-matrix thesaurus, it searches the text set for the concepts denoted in the meta-matrix thesaurus and translates matches into the corresponding meta-matrix entity classes as specified by the analyst. When performing meta-matrix text analysis, AutoMap links the meta-matrix entity classes in the texts that were pre-processed with a meta-matrix thesaurus into statements, and builds one concept network per text that is cross-coded in terms of the meta-matrix, thus resulting also in a meta-matrix. This automated network creation is step 4, perform map analysis, in the coding procedure.

The resulting networks can be analyzed at varying levels during step 5, graph and analyze data. For example, the analyst might be interested in seeing and analyzing the networks of the text-level concepts that represent all or only some of the meta-matrix categories. We implemented this functionality as sub-matrix text analysis. Each cell in Table 3 denotes a sub-matrix. Sub-matrix analysis distills one or several sub-networks from the meta-matrix and presents text-level concepts in the chosen entity classes. This routine enables a more thorough analysis of particular sections of the meta-matrix, such as Agent-by-Agent networks (social networks), or Organization-by-Resource networks (organizational capability networks). When performing sub-matrix text analysis, AutoMap links the concepts representing the meta-matrix entity classes selected by the analyst into networks.

With the implementation of meta-matrix text analysis and sub-matrix text analysis in AutoMap, we hope to contribute to the investigation of the network structure of social and organizational systems that are represented in texts. With these techniques we aim to provide a reasonable extension of the base technology of computer-supported network text analysis and a practical implementation of the meta-matrix model. In the next section we demonstrate how these novel techniques can help analysts to detect the meaning and underlying social structure inherent in textual data in order to answer related research questions.

## **Illustrative Example of the Application of Network Text Analysis**

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To demonstrate the meta-matrix approach to NTA we use a small sample data set of 18 texts. Each text will be coded using the proposed approach and the AutoMap software.

### **Data**

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This text sample is a sub-sample drawn from a larger text collection that consists of 191 texts collected at CASOS about six major terrorist groups that operate in the West Bank. These groups are the Al Aksa Martyrs Brigades, Al Fatah, Al Qaeda, Hamas, Hezbollah, and the Islamic Jihad. We gathered the texts from LexisNexis Academia via exact matching Boolean keyword search for each of the groups. The media that we searched with LexisNexis were *The Economist*, *The Washington Post*, and *The New York Times*. The time frame of our data set ranges from articles published in 2000 to 2003. We sorted the retrieved texts by relevance, screened the top most texts, and selected up to three texts per organization and year for our dataset. The sub-sample from this corpus that we work with in this chapter consists of one text per terror group from each medium from 2003 (Table 4). This sub sample of 18 texts contains 3,035 unique concepts and 13,141 total concepts. The number of unique concepts considers each concept only once, whereas the number of total concepts also counts repetitions of concepts. The reader should keep in mind that the small size of this data set and the fact that the texts were chosen across groups rather than within groups is likely to lead to more overall concepts and fewer

step 5, graph and analyze the network structure of social relations among them. A discussion of Hamas and Yassin may be unlikely to refer to a discussion about al Qaeda and bin Laden; whereas, it is more likely to refer to Rantissi. This text set is a suitable illustrative example because the detection of covert networks such as terrorist groups is one application domain for meta-matrix analysis (Carley, Dombrowski, Tsvetovat, Reminga & Kamneva, 2003). Since texts are a widely used source of information about terrorist groups, a technique for pulling networks classified according to the meta-matrix scheme from this type of data is needed. The results of this sample study are neither a valid indication of these terrorist groups nor a formal validation of the method of meta-matrix text analysis, but show what information the analyst can gain from this novel technique.

meta-matrix text analysis in the work structure of social relations among these techniques we aim to enhance the quality of computer-supported meta-matrix model. In the next step analysts to detect the network structure in order to answer related

## Application

all sample data set of 18 texts from the AutoMap software.

text set that consists of 191 texts extracted from the West Bank. The text set includes Hamas, Hezbollah, and al Qaeda via exact matching. The text set that we searched with AutoMap from the *New York Times*. The time period is from 2003 to 2003. We sorted the texts selected up to three texts from this corpus that we work with each medium from 2003 to 2003. The total number of concepts and 13,141 total concepts. The reader should keep in mind that the texts were chosen across all concepts and fewer

text forms without written

### *Data Pre-Processing (Concept Identification)*

The quality of the map (or network) extracted from the text can be enhanced by pre-processing the data prior to running the analysis: Text pre-processing condenses the data to the concepts that capture the features of the texts that are relevant to the analyst. This technique is also the first step in the procedure of performing meta-matrix text analysis (see section 4). In a previous publication we have described text pre-processing strategies and results with AutoMap in detail (Diesner & Carley, 2004). As a first pre-processing technique we applied a delete list customized for this dataset<sup>1</sup>. Deletion removes non-content bearing concepts such as conjunctions and articles from texts (Carley, 1993). This reduces the number of concepts the analyst needs to consider when forming thesauri. Then we stemmed the texts with the AutoMap stemmer, which is based on the Porter Stemmer (Porter, 1980). Stemming detects inflections and derivations of concepts in order to convert each concept into the related morpheme (Jurafsky & Martin, 2000). Stemming simplifies the process of constructing a generalization thesaurus and can often eliminate spelling errors and typos. Then we used AutoMap's Named-Entity Recognition functionality. Named-Entity Recognition retrieves concepts such as proper names, numerals, and abbreviations contained in a text set (Magnini, Negri, Prevete & Tanev, 2002). This technique helps to index agents, organizations, places, and events and facilitates building the meta-matrix thesaurus. There were 591 named entities in our dataset. This list of named entities was used to:

1. Translate relevant phrases into a unit that will be recognized as a single concept. This can be realized in the generalization thesaurus in AutoMap by, e.g., replacing the spaces by words that are separated with underscores.

*Table 4. Dataset — number of texts that terror group appears in*

Source	Aksa	Fatah	Hamas	Hezbollah	Islamic Jihad	al Qaeda
The Washington Post	2	1	2	1	1	2
The New York Times	1	2	3	2	2	1
The Economist	1	2	4	1	2	1
Total	4	5	9	4	5	4

Examples:

Holi War into Holy\_War. The apparent misspelling of Holi results from stemming.

Golan Height into Golan\_Heights.

2. Translate people's names, various versions of their names as they appear in the data set, aliases and synonyms that these people use into the organization that this person is associated with.

Examples:

Dr. Abdel Aziz Rantisi and Dr. Rantisi into Aziz\_Al-Rantisi, who is a member of Hamas.

Mahmoud Abba and Abu Mazen into Mahmoud\_Abbas, who is a member of the Palestinian Authority.

3. Translate various spellings of a group and synonyms for groups into one unique name of the related group or organization.

Examples:

Hizbullah into Hezbollah.

Islamic Resistance Movement into Hamas.

## Thesaurus Creation

The resulting 170 pairs of associations of text-level concepts with higher-level concepts formed a generalization thesaurus. As noted, a generalization thesaurus translates text-level concepts into higher-level concepts. A single higher-level concept typically has multiple text-level entries associated with it in a thesaurus. For example, Imad Falouji (the higher-level concept), a Hamas member, appeared in the text set as Imad Falouji and Mr. Falouji (two related text-level concepts). The more text-level entries are associated with a higher-level concept, the greater the level of generalization being employed by the analyst.

Since no pre-defined thesaurus was available to us that would have matched terrorism-related concepts to meta-matrix entity classes, we built a second generalization thesaurus. After applying the generalization thesaurus, we built and applied a second generalization thesaurus with 50 entries that translates people's names into organizations or more abstract groups with which these people are associated. We used four basic guidelines:

1. Members of the six terrorist groups that the data set focuses on into the related terrorist organization.

Examples:

Aziz Al-Rantisi into Hamas.

2. Representatives of the governments of various countries into the country's government.

Examples:

Omar Sulieman into Egypt\_Government.

Mahmoud Abbas into Palestinian\_Authority.

3. People's names into organizations or abstract groups that they belong to.

Examples:

Hans\_Blix, Kofi\_Annan, and Michael\_Chandler into UN.

Hanadi Jaradat and Saed Hanani into Suicide\_Bomber.

Haviv\_Dodon, Muhammad\_Faraj

Samer\_Ufi into Victim\_Killed.

In doing this, the basic principle we were applying was to retain specific actors — those who appeared to play primary roles, whereas secondary actors were reclassified by their role, such as victim. Not all names of people that can be associated with a group were translated into the related group. We applied this strategy in order to enable us to retranslate the entity class Agent, to which we assigned these names in the meta-matrix thesaurus that we applied after the second generalization thesaurus, into the names of key players relevant to us in a sub-matrix text analysis that can be run after the meta-matrix text analysis. Names that we decided not to match with an organization are for example Osama bin Laden, Yasser Arafat and Ariel Sharon. This level of maintenance of detail of information always depends on the research question or goal. Our goal was to detect the network structure of terrorist groups.

After finishing the generalization process<sup>2</sup> we built and employed a meta-matrix thesaurus. In order to support the analyst in matching text-level concepts against meta-matrix categories, AutoMap offers the options to: a) load a list of all unique concepts appearing in the text set into the left most column of the meta-matrix thesaurus or b) save a list of a union of all unique concepts on a directory of the analyst's choice. In the next step the analyst has to manually go through this list and to decide whether or not to associate each single concept with meta-matrix categories. Our dataset contained 2,083 unique concepts after applying the generalization thesauri. Of these unique concepts, 303 were assigned to a single entity class in the meta-matrix, and 23 of them to two entity classes (Table 5, sum of column one). A total of 1780 of the 2083 unique concepts we did not assign to any meta-matrix entity class, but they were kept as non-categorized concepts. The creation of a meta-matrix thesaurus is step 3, concept classification, in the procedure of performing meta-matrix text analysis (see section 4).

Table 5. Creation and application of meta-matrix thesaurus (sorted by frequency)

Category	Cumulated sum of assignment of concepts to entity classes in the meta-matrix thesaurus	Cumulated sum of appearance of entity classes in texts after application of meta-matrix thesaurus	Cumulated sum of linkage of concepts associated with meta-matrix entity classes into statements
Organization	48	569	434
Location	81	404	404
Agent	54	250	217
Resource	75	261	188
Task-Event	27	168	146
Knowledge	41	134	128

In the next step we applied the meta-matrix thesaurus to the data set<sup>3</sup> and ran a meta-matrix text analysis on the pre-processed text set<sup>4</sup>. This technique forms step 4, perform map analysis, in the procedure of performing meta-matrix text analysis (see section 4).

## Characteristics of the Textual Networks as Meta-Matrices (Graph and Analyze Results)

In this section, we report the results of the meta-matrix text analysis and sub-matrix text analysis we ran on our data set. This task is step 5 in the procedure of performing meta-matrix text analysis. The intent in this section is to illustrate the type of results and graphs possible using the proposed meta-matrix approach to NTA, not to present a comprehensive analysis of terrorist networks. In doing this example, we will analyze: 1) unique and total frequencies of the concepts and statements, 2) unique and total frequencies of the statements that were formed from concepts associated with meta-matrix entity classes, and 3) the distribution of statements formed from meta-matrix entity classes across the data set.

For our analysis we considered the six meta-matrix entity classes in Table 3. Therefore, we have six unique entity level concepts. Considering only concepts that fall into one or more of these categories, we found an average of 99.2 total concepts per text, ranging from 37 to 163. Based on these concepts, on average of 18.9 unique statements (ranging from 8 to 29) and 45.7 total statements (ranging from 12 to 84) were formed per text. Thus, on average, each unique statement appeared 2.4 times per text. Theoretically, each text could contain up to 36 unique statements. The theoretic maximum would be achieved if there existed at least one concept associated with each entity, and at least one concept of each entity formed a statement with at least one concept in each other entity class. The multiple occurrences of unique statements are expressed in the number of total statements.

Across the 18 meta-matrices extracted from our sample texts, 822 total statements were formed within and between the cells of the meta-matrix (see Table 6 for distribution of total statements across meta-matrix). Notice that the upper and lower triangle of the meta-matrix in Table 6 are not symmetric. For example, in Table 6 from Resource (row) to Organization (column) there are a total of 23 statements, but from Organization (row) to Resource (column) there are a total of 35 statements. Indeed, there is no need for symmetry as the relations between concepts (edges between nodes) found with AutoMap are directed, which is inherently pre-defined by the directed structure of language. The results in Table 6 show that concepts associated with each meta-matrix entity class appears approximately as often in posterior positions of statements (last row in Table 6) as in anterior positions (last column in Table 6). Thus, the in-degree or receptivity of a meta-matrix entity class approximately equals the out-degree or expansiveness of the class. This is due, in part, to the use of proximity in the text to place links among concepts and reflects, if anything, the lack of overly stylized sentential form.

Within the meta-matrix, the entity class that linked most frequently to other entity classes was Organization (179 links), followed by Location (108), Agent (95), Resource (71), Task-Event (66), and Knowledge (53). If we do not look at these absolute values, but at percentages of the linkage of meta-matrix entity classes to the same or other entity classes, our results reveal that concepts in the entity class Task-Event are more likely to be connected to concepts in classes other than Task-Event. In contrast to Task-Event, concepts in the entity class Location are most likely to link to other Location concepts (Table 7).

Furthermore, the results indicate that within the networks that we extracted from the texts, most information refers to membership networks (13.8% of all statements, Figure 1).

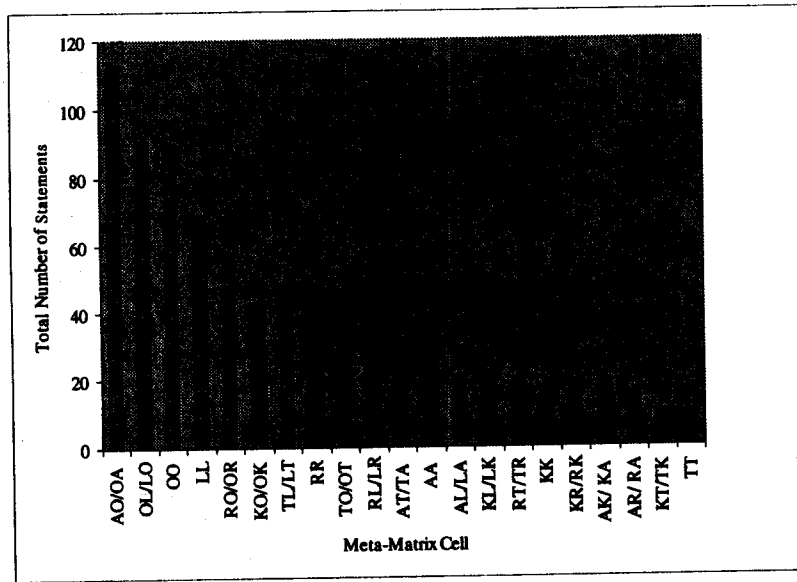
Table 6. Number of links (total number of statements) between meta-matrix categories

Meta-Matrix	Agent	Knowledge	Resource	Task-Event	Organization	Location	Sum
Agent	24	8	8	12	55	12	119
Knowledge	10	18	9	3	20	11	71
Resource	8	9	39	11	23	20	110
Task-Event	13	7	9	10	20	17	76
Organization	58	23	35	19	90	44	269
Location	9	10	17	25	47	69	177
Sum	122	75	117	80	255	173	822

Table 7. Linkage of meta-matrix entity classes

Meta-Matrix entity class	With same entity class (%)	With other entity classes (%)
Task-Event	13	87
Agent	20	80
Knowledge	25	75
Organization	33	67
Resource	35	65
Location	39	61

Figure 1: Total number of links between meta-matrix categories



Although there is also substantial information on inter-organizational networks (11.1%) and organizational location networks (10.4%). The least information is provided on precedence networks (1.2%) and knowledge requirement networks (1.2%). This suggests that more is known, or at least presented in the news, about who the terrorists are and where they are than about what they do when and what they need to know in order to engage in such actions or why.

The analysis of the distribution of statements formed from meta-matrix entity classes across the text set reveals that all entities are covered in at least one third of the texts. In addition, Organization, Location, and Agent classes appear in more than half of the texts (Table 8). Again, this suggests that more is reported about who and where than about what, how and why. We note that a human reading of these texts may pick up a little more about what and how, although such information does appear to be less common in general in the texts used for this purely illustrative analysis.

Table 8: Number of texts in that links appears

Meta-Matrix	Agent	Knowledge	Resource	Task-Event	Organization	Location	Sum
Agent	13	5	6	10	17	9	10.0
Knowledge	7	9	5	3	9	5	6.3
Resource	4	4	9	7	12	11	7.8
Task-Event	9	3	7	4	11	10	7.3
Organization	17	11	13	11	18	16	14.3
Location	7	7	10	11	17	14	11.0
Sum	9.5	6.5	8.3	7.7	14.0	10.8	9.5



In Figure 1 and Tables 6 and 8, we have been discussing the total links or statements. Looking at the total links provides information about the overall structure of the discussion and the elements of the structure (agents, knowledge, etc.) that are considered critical by the authors or for which they have a wealth of information. It is often useful to ask about unique links, however, if we want to understand the structure itself. In Figure 2, we display the number of links per sub-matrix that are unique. That is, a link or statement is only counted once regardless of how many texts it appears in.

Comparison of Figures 1 and 2 shows that a great deal of information — particularly in the Agent-to-Agent sub-matrix is repeated across texts. This suggests that either many of the texts were discussing the same information (repetition), or they got their information from the same source. Note that if we knew that each source was unique, then the difference between the total (Figure 1) and the unique (Figure 2) would be an indicator of the reliability of the information.

The overall structure for this covert network is very sparse. In some sense, based on these texts, more is known about the affiliations, locations, resources, and knowledge of agents and organizations than is known about the interrelations of knowledge, resources and tasks (Table 9). Further, if we compare the number of unique links (Table 9) to the number

Figure 2. Number of unique links between meta-matrix categories

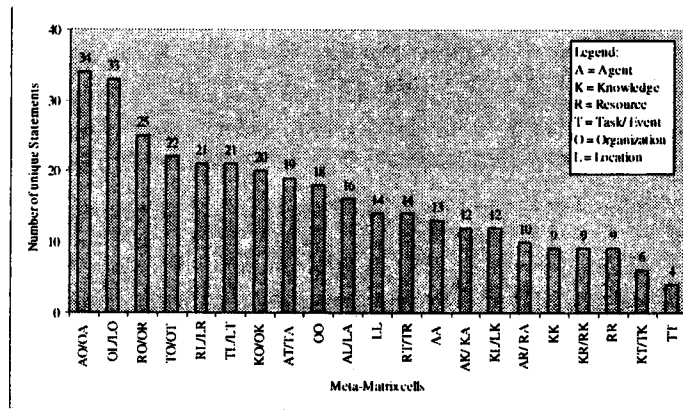


Table 9. Number of links (unique number) between meta-matrix categories

Meta-Matrix	Agent	Knowledge	Resource	Task-Event	Organization	Location
Agent	13	12	10	19	34	16
Knowledge		9	9	6	20	12
Resource			9	14	25	21
Task-Event				4	22	21
Organization					18	33
Location						14

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n	Location	Sum
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	5	6.3
	11	7.8
	10	7.3
	16	14.3
	14	11.0
	10.8	9.5

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of texts that contain links (for each sub-matrix) (Table 8) we see that the two tables are similar. In other words, many links appear in only one text. It is interesting to note which sub-matrices have more unique links than texts – e.g., the Agent-by-Knowledge and the Organization-by-Knowledge sub-matrices. This indicates that the texts that discuss the knowledge network tend to do so by discussing multiple linkages (e.g., all of these people know item z). Whereas texts that discuss, e.g., the social network (Agent-by-Agent) are more likely to simply talk about a single pair of actors and the nature of their relationship. Whether this pattern of reporting would hold in other cultures is debatable.

Beyond learning about the network structure of the meta-matrices and the distribution of concepts and connections between them across the sample data, analysts might be interested in investigating in more detail the concepts and links contained in the meta-matrix. In order to gain this knowledge, sub-matrix text analysis<sup>5</sup> can be run. For

*Table 10: Who has what means? Organizational capability network (organization by resource)*

Statements formed from Higher-Level Concepts (Sub-Matrix Analysis)	
Sample text 1:	Sample text 2:
1 Al-Qaeda – training camp	1 Al-Aksa - assets
1 network- Hawala	1 Al-Aksa - money
1 Hawala – money	1 Hamas - sponsoring
1 finance – network	1 aid - Hamas
1 camp - US-Government	1 aid - Treasury Department
	1 money - Hamas
	1 support - Hamas
	1 Treasury - assistance
	1 US-Government - assistance
	1 assets - Treasury Department

*Table 11: Who knows what? Knowledge network (agent by knowledge)*

Statements formed from Higher-Level Concepts (Sub-Matrix Analysis)	
Sample text 1:	Sample text 2:
1 chairman – monitoring	1 FBI - Analyst
1 evidence – Saddam Hussein	

*Table 12: Who is located where and does what? (Localized assignment network: agent by task-event by location)*

Statements formed from Higher-Level Concepts (Sub-Matrix Analysis)	
Sample text 1:	Sample text 2:
1 Saddam Hussein - Iraq	1 arrest - Leader
	1 Leader - Germany

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illustrating the results of this procedure, we show a map from the same text in Tables 10 to 12. A map contains one coded statement per line and its frequency.

These various sub-matrix networks enable a better understanding of what attributes of the meta-matrix link to other attributes, and with what strength. All three sub-matrices together enable a broader view of the situation. Figures 3 and 4 illustrate this broader picture. The comparison of figures 3 and 4 illustrates that text 1 presents a more disconnected story than does text 2. Further, even if the two stories were combined, the

Figure 3: Visualization of sub-matrices from sample text 1

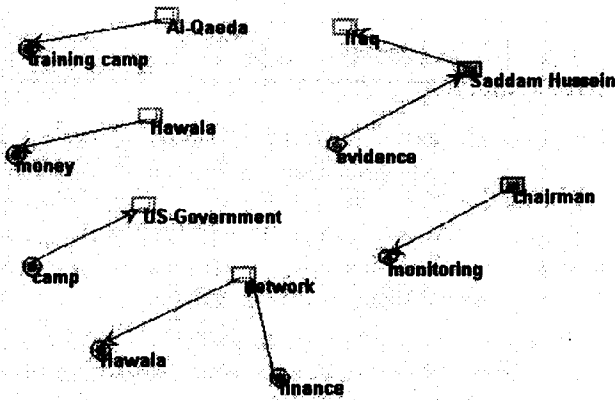
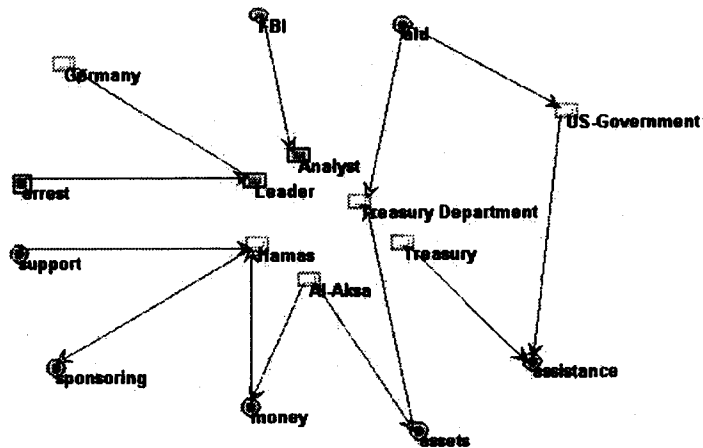


Figure 4: Visualization of sub-matrices from sample text 2



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overall map would tell us little about the structure of the two terrorist groups — al-Qaeda and Hamas.

Meta-matrix data and sub-matrix data generated with AutoMap can be saved and then re-analyzed outside of AutoMap using standard social network analysis tools. AutoMap can both code these networks and then output them in two useful exchange formats for use with other network analysis tools — DL for UCINET and DyNetML for ORA ([www.casos.cs.cmu.edu/projects/ORA](http://www.casos.cs.cmu.edu/projects/ORA), Carley and Reminga, 2004). For this chapter, we use ORA as it enables the analysis of all the cells in the meta-matrix at once. In either case, the combination of text and network analysis enables the analyst to readily combine rich textual data with organizational data connected through other methods, thus enhancing the analysis process.

## **Discussion-Features and Limitations**

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The techniques of meta-matrix text analysis and sub-matrix text analysis described herein can support analysts in investigating the network structure of social and organizational systems that are represented in textual data. Furthermore, these novel and integrative methods enable analysts to classify words in texts into entity classes (node types) associated with networks common to organizational structures according to a theoretically and empirically validated ontology — the meta-matrix.

The validity of the method and the results presented in this chapter are constrained by the little experience we gained so far with these novel techniques, the small number of texts analyzed, and the implementation of the techniques into one software. The tool should also be applied to multiple larger data sets.

## **Lessons Learned**

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In general, we find that the entity-name recognizer greatly enhances the ability to locate concepts associated with the meta-matrix ontology. In particular, it facilitates locating Agents, Organizations, and Locations. For entity classes that are less associated with proper nouns, the name recognizer is of less value.

Coding texts using AutoMap is not a completely automated process. However, AutoMap does provide a high degree of automation that assists the user and increases the efficiency and effectiveness of meta-matrix text analysis in comparison to manual coding. As with most text analysis techniques that seek to extract meaning, significant manual effort needs to be expended on constructing the delete list and thesauri, even though the method is computer-supported. For example, the delete list used in this study took 30 minutes to construct. However, the thesauri (and there are three) took four days to construct. Thesauri enable the minimization of miscoding, as in missed relations, due to aliases and misspellings, and differences due to the underlying languages. Analysts have to decide on an optimal trade-off between speed of the computer-supported

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research process and enhancement of the quality of automated coding caused by the manual creation and refinement of pre-processing tools according to their goals and resources.

It is worth noting that significant improvement over straight manual coding can be achieved by building thesauri and delete lists based on only a fraction of texts. As more texts in this domain are coded, we will have to expend relatively little additional effort to expand the delete and thesauri list. For example, we suspect that hundreds of additional texts will be codable with maybe only a day more attention to the thesauri. The reason is that, when in the same domain, construction of thesauri is like building a sample via the snowball method (i.e., with each iteration fewer and fewer novel concepts are found). How large that fraction should be is a point for future work. However, preliminary studies suggest 10% is probably sufficient. Future work should explore whether intelligent data mining and machine learning techniques can be combined with social network analysis and text analysis to provide a more automated approach to constructing thesauri on the fly.

We also find that the higher the level of generalization used in the generalization thesaurus, the greater the ability to compare two diverse texts. Not counting typographical errors, often the translation of two to ten text-level concepts per high-level concept seems sufficient to generate a “language” for the domain being studied.

We note that when forming thesauri, it is often critical to keep track of why certain types of concepts are generalized into others. At the moment there is no way to keep that rationalization within AutoMap. In general, the user should keep a lab notebook or readme file for keeping such rationalizations.

Finally, we note that for extracting social or organizational structure from texts a large corpus is needed. The point here is comprehensiveness, not necessarily a specific number of texts. Thus, one might use the entire content of a book that describes and discusses an organization or a large set of newspaper articles. In building this corpus, not all texts have to be of the same type. Thus, the analyst can combine newspaper reports, books, board-of-directors reports, Web pages, etc. Once the networks are extracted via AutoMap they can be combined into a comprehensive description of the organization being examined. Further, the analyst needs to pre-define what the basic criteria are for including a text in the corpus — e.g., it might be publication venue, time frame, geographic area, specific people, organizations, or locations mentioned.

## Considerations for Future Work

We also note that the higher the level of generalization, the more ideas are being inferred from, rather than extracted from, the texts. Research needs to be done on the appropriate levels of generalization. Note that the level of generalization can be measured as the average number of text-level concepts associated with each higher level concept.

One of the strengths of NTA is that the networks extracted from the texts can be combined in a set theoretic fashion. So we can talk about the network formed by the union or intersection of the set of networks drawn from the set of texts. When combining these

networks we can, for each statement, track the number of texts that contained that statement. Since a statement is a relation connecting two concepts, this approach effectively provides a weight for that relation. Alternatively, the analyst can compute whether any text contained that statement. In this case, there are no weights and the links in the network are simply present or not (binary). If these texts represent diverse sources of information, then the weights are indicative of the certainty or verifiability of a relation. Future work might also explore utilizing Bayesian learning techniques for estimating the overall confidence in a relation rather than just summing up the number of texts in which the statement was present.

We also note that when people read texts there is a process of automatic inference. For example, when people read about a child talking to a parent they infer based on social experience that the child is younger. Similarly, it appears that such inferences are common between the entity classes. For example, if Agent X has Resource Y and Knowledge K is needed to use Resource Y, then in general Agent X will have Knowledge K. Future work needs to investigate whether a simple inference engine at the entity class level would facilitate coding. We note that previous work found that using expert systems to assist coding in terms of adding general social knowledge was quite effective (Carley, 1988). Thus, we expect this to be a promising avenue for future research.

Finally, we note that the use of an ontology adds a hierarchical level to the coding. This is invaluable from an interpretative perspective. There is no reason, conceptually, why multiple hierarchical levels could not be added, denoting finer and finer levels of detail. We suspect however, based on the use of hierarchical coding schemes in various scientific fields (e.g., biology and organization theory) that: a) such hierarchies are likely to not be infinitely deep, b) a certain level of theoretical maturity and consensus in a field is needed for such a hierarchy to be generally useful, and c) eventually we will need to move beyond such a "flat" scheme for extracting meaning. As to this last point, by flat what we are referring to is the fact that a hierarchy can be completely represented in two dimensions. We found, even when doing this limited coding that some text-level concepts and higher-level concepts needed to be cross-classified into two or more entity classes. As more levels are added in an ontological hierarchy, such cross classification is likely to occur at each level, resulting in a network of inference, not a simple hierarchy and so a non-flat structure. Future work should examine how to code, represent, and reason about such networks.

## **Conclusion**

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One of the key advantages of classic content analysis was that macro social change could be tracked by changes in content, and over- or under-representation of various words. For example, movements toward war might be signaled by an increasing usage of words describing hostile acts, foreign powers, and weapons. One of the key advantages of Network Text Analysis (NTA) over standard text analysis is that it enables the extraction of meaning and enables interpretation by signaling not just what words are used but how

they are used. This enables differences and similarities in viewpoints to be examined, and it enables the tracking of micro social change as evidenced by changes in meaning. By adding an ontology to NTA, differences and similarities in viewpoints about a meta-structure described or discussed in the text can be examined.

In this chapter, we used the meta-matrix ontology as we were interested in the underlying social/organizational structure described in the texts. Several points are critical to note. First, the mere fact that we used an ontology to define a set of meta-concepts enables the extraction of a hierarchy of meaning thus affording the analyst with greater interpretive ability. Second, any ontology could be used, and the analyst needs to consider the appropriate ontology for their work. In creating this ontology the analyst wants to think in terms of the set of entity classes and the relations among them that define the second level network of interest. For us, these entity classes and relations were those relevant to defining the organizational structure of a group.

The proposed meta-matrix approach to text analysis makes it possible to track more micro social change in terms of changes, not just in meaning, but in the social and organizational structures. Using techniques such as this facilitates a more systematic analysis of groups, broadens the types of questions that can be effectively answered using texts, and brings the richness of textual information to bear in defining and understanding the structure of the organizations and society in which we live.

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## Endnotes

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- 1 The delete list was applied with the rhetorical adjacency option. Rhetorical adjacency means that text-level concepts matching entries in the delete list are replaced by imaginary placeholders. Those place holders ensure that only concepts, which occurred within a window before pre-processing, can form statements (Diesner & Carley, 2004).
- 2 We did not choose the thesaurus content only option. Thus, adjacency does not apply.
- 3 We used the thesaurus content only option in combination with the rhetorical adjacency. Thus, the meta-matrix categories are the unique concepts.
- 4 We used the following statement formation settings: Directionality: uni-directional, Window Size: 4, Text Unit: Text (for detailed information about analysis settings in AutoMap see Diesner & Carley, 2004).

<sup>5</sup> Sub-Matrix selection was performed with the rhetorical adjacency option.

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## Appendix

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Software: AutoMap: Diesner, J. & Carley, K.M. (2004). *AutoMap1.2: Software for Network Text Analysis*.

AutoMap is a network text analysis tool that extracts, analyzes, represents, and compares mental models from texts. The software package performs map analysis, meta-matrix text analysis, and sub-matrix text analysis. As an input, AutoMap takes raw, free flowing, and unmarked texts with ASCII characters. When performing analysis, AutoMap encodes the links between concepts in a text and builds a network of the linked concepts. As an output, AutoMap generates representations of the extracted mental models as a map file and a stat file per text, various term distribution lists and matrices in comma separated value (csv) format, and outputs in DL format for UCINET and DyNetML format. The scope of functionalities and outputs supported by AutoMap enables one way of analyzing complex, large-scale systems and provide multi-level access to the meaning of textual data.

**Limitations:** Coding in AutoMap is computer-assisted. Computer-assisted coding means that the machine applies a set of coding rules that were defined by a human (Ryan and Bernard, 2000, p.786; Kelle, 1997, p. 6; Klein, 1997, p. 256). Coding rules in AutoMap imply text pre-processing. Text pre-processing condenses the data to the concepts that capture the features of the texts that are relevant to the user. Pre-processing techniques provided in AutoMap are Named-Entity Recognition, Stemming, Deletion, and Thesaurus application. The creation of delete lists and thesauri requires some manual effort (see Discussion section for details).

Hardware and software requirements: AutoMap1.2 has been implemented in Java 1.4. The system has been validated for Windows. The installer for AutoMap1.2 for Windows and a help file that includes examples of all AutoMap1.2 functionalities are available online under <http://www.casos.cs.cmu.edu/projects/automap/software.html> at no charge. More information about AutoMap, such as publications, sponsors, and contact information is provided under <http://www.casos.cs.cmu.edu/projects/automap/index.html>.

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AutoMap has been written such that the only limit on the number of texts that can be analyzed, the number of concepts that can be extracted, etc., are determined by the processing power and storage space of the user's machine.